



Autonomous Quadcopter Drone Race

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Abstract

This project develops a fully autonomous mobility stack for mid-sized quadrotor drones designed for high-speed racing. Using COEX Clover drones equipped with onboard sensors and an Arducam 100 fps mono global shutter camera, the system enables vision-based navigation through multiple race checkpoints. Implemented in the Robot Operating System (ROS), the autonomy stack integrates localization, perception, path planning, and control. Initially validated using a ViCON motion tracking system, the setup now achieves fully onboard operation using ArUco marker-based localization and YOLO-based checkpoint detection.

The multi-modal control layer combines a Model Predictive Controller (MPC) for precise trajectory tracking and a Reinforcement Learning (RL) model for agile decision-making. The RL racing policy, trained for 140 million steps across lightweight simulation and Gazebo, achieves average speeds of 2.85 m/s with peaks of 4.16 m/s. A neural network-trained MPC is converted to TensorFlow Lite and deployed on a Raspberry Pi 4 for real-time execution. The result is an end-to-end, vision-driven, learning-enabled drone platform capable of fast, agile, and fully autonomous flight.

Objectives

Build a Fully Autonomous Stack

- Integrate localization, perception, planning, and control within ROS for mid-sized quadrotors

Enable Onboard Vision

- Deploy ArUco marker-based localization and YOLO checkpoint detection—no external tracking

Develop Dual Control Modes

- Combine MPC for stable trajectory tracking with RL for aggressive racing maneuvers

Deploy on Embedded Hardware

- Convert neural network MPC to TensorFlow Lite for real-time execution on Raspberry Pi 4

Validate Through Sim-to-Real Pipeline

- Train in lightweight simulation → fine-tuned in Gazebo → tested on physical hardware

Achieve High-Speed Autonomous Flight

- Demonstrate vision-driven racing with onboard compute at competitive speeds

Materials and Methods

Hardware

- COEX Clover Drone 4.2
- Raspberry Pi 4 Model B
- PTK Votek 9497 Servo
- Arducam 100fps Mono Global Shutter USB Camera
- XYG-Raspberry Pi R Camera
- Power Distribution Board
- MR30 connector (for motor speed control)
- Gemfan Drone racing gates

Software

- ROS Noetic
- Simulation/Model Acquisition
- Gazebo version 11.15.1
- Python 3.9
- Tensorflow version 2.13.0
- TF-agents version 0.17.0
- Numpy version 1.24.3
- Nvidia CUDA Development Kit 11.8
- Gymnasium version 0.29.1

Diagrams/Figures/Experiments

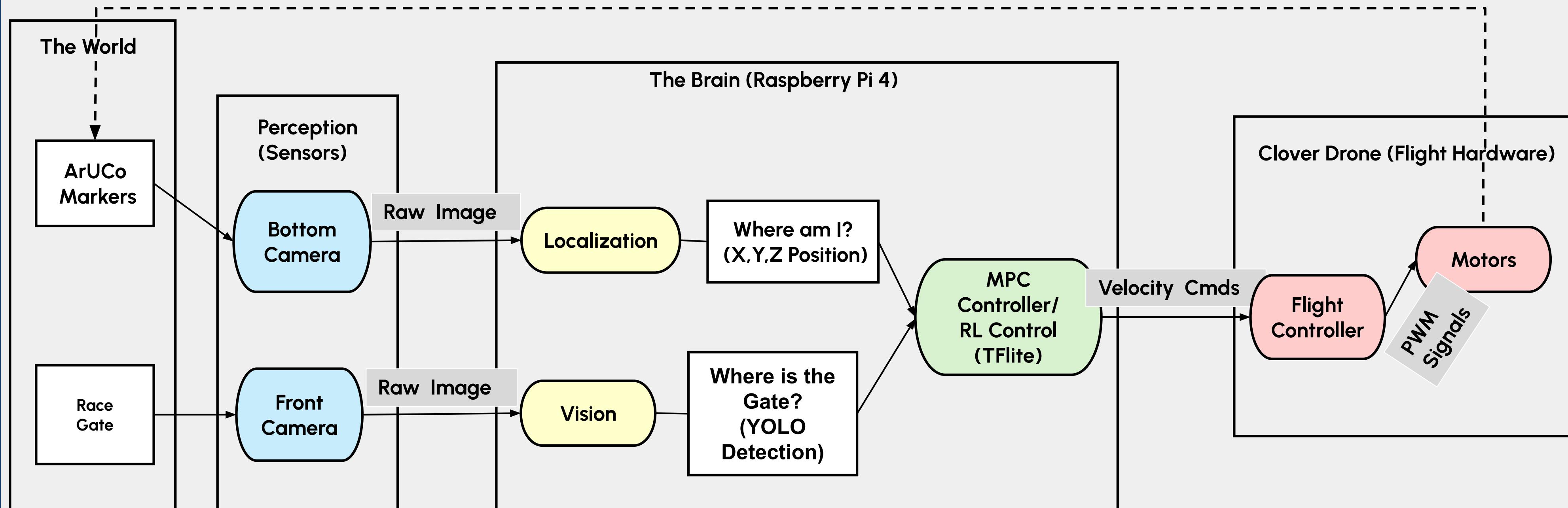


Fig 1: System Architecture

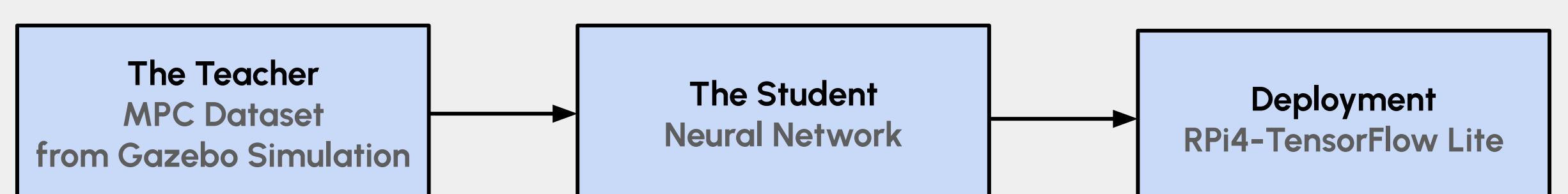


Fig 2: MPC Deployment Strategy

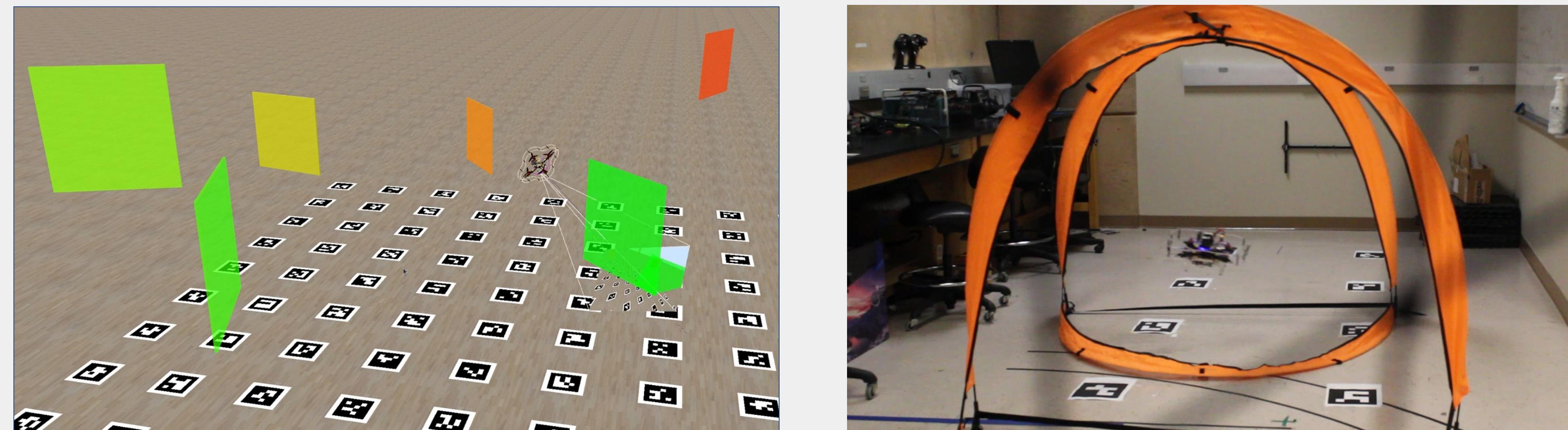


Fig 3(a): Drone Flying in Gazebo Simulator

Fig 3(b): Drone Flying between Gates in Real World

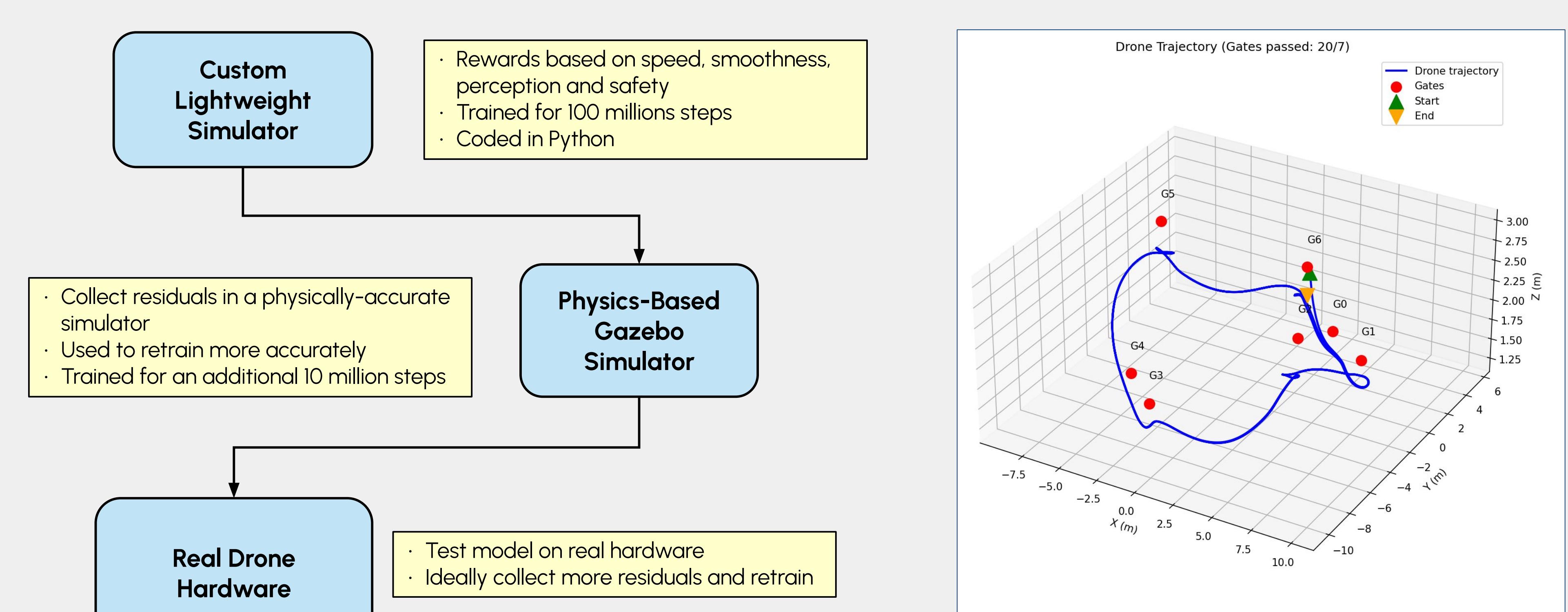


Fig 4(a): RL Simulation to Real Pipeline

Fig 4(b): RL Racing Model Visualization

Results

Model Predictive Control: Experimental Results

- Validated core MPC logic by implementing a Z-axis (altitude) controller in Gazebo – performed as expected.
- Expanded to a full 3D MPC, achieving stable and accurate flight along linear trajectory with minor deviations.
- During sharp turns (e.g., 90° corners), the drone failed to execute precise maneuvers, often cutting corners or missing gates.

RL Racing Model Control: Experimental Results

- Racing model trained for 140 Million Steps in lightweight custom sim, able to lap racetrack multiple times per 1500 steps
- Achieves average speed of 2.85m/s and top speed of 4.16m/s



Fig 5a (Left): Perception Reporting Gate Location

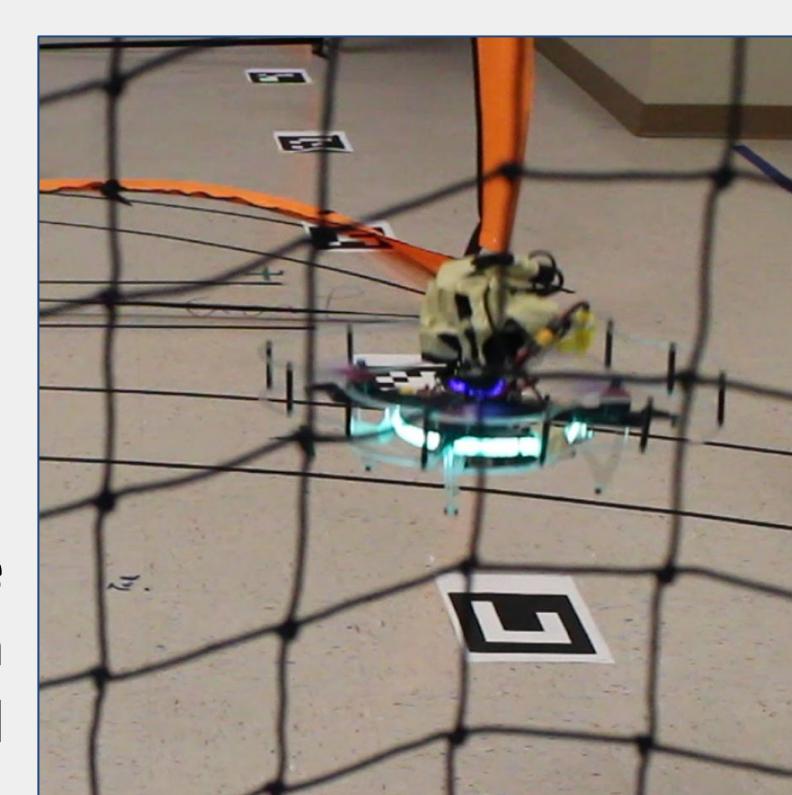


Fig 5b (Right): Drone Flying with Perception Hardware Attached

YOLO-based perception model : Experimental Results

- Validated Gates/Object detection using YOLO in real-time with high accuracy.
- Successfully calculating accurate distance from Arducam camera to Gate using pixel calculation method, and further generating target co-ordinates i.e. gate coordinates, assuming camera as epi-center.

Additional Information

- This project is supervised by Prof. Yasser Shoukry at the Resilient Cyber-Physical Systems Lab, UC Irvine

| Team Member | Key Contribution |
|----------------------|---|
| Aneri Hiren Desai | MPC Development, MPC Neural Network Model Development, Testing and Training of NN model |
| Derek Tran | Drone Management and AI Camera |
| Isaiah Cabugos | RL Development, Localization calibration, Flight Control Configuration and Testing |
| Jasera Abdurashid | MPC training, ROS Simulation and Testing |
| Rohankumar Barouliya | Camera integration, YOLO pipeline, Target distance estimation |

References

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- AirPilot: Interpretable PPO-based DRL Auto-Tuned Nonlinear PID Drone Controller for Robust Autonomous Flights : <https://arxiv.org/abs/2404.00204>
- Actor-Critic Model Predictive Control: Differentiable Optimization meets Reinforcement Learning: https://rpg.ifif.uzh.ch/research_drone_racing.html
- You Only Look Once: Unified, Real-Time Object Detection: https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Redmon_You_Only_Look_CVPR_2016_paper.pdf
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